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Hybrid Model Based on User Tags and Textual Passwords and Pearsonian Type III Mixture Model

Pavan Gujjar Panduranga Rao[1], Dr.P.Srinivasa Rao[2], Dr. G. Lavanya Devi[3]

[1]Research Scholar, Department of Computer Science and System Engineering, Andhra University College of Engineering (A),Vishkhapatanam, Andhra University, India

[2,3]Professor, Department of Computer Science and System Engineering, Andhra University College of Engineering(A), Andhra University, Vishkhapatanam, Andhra Pradesh, India

***Abstract*— *The latest advancements in Science and Technology, have witnessed radical changes in the banking system. Today most of the banks adopt the net banking facility and most of the users are also addicted to this system. Accordingly, most of the transactions are now online based and much emphasis is therefore needed to ensure the security of authenticating a person and validating the transaction. Many models are therefore proposed in the literature. Most of these are an alphanumeric based password schemes or biometric schemes or graphical password based schemes. Each of these models is proposed by underlying an advantage. The alphanumeric passwords are proposed, with the assumption that generating the password is easy and the generated password is unique, the biometric password schemes are proposed with the assumption that tampering a biometric is next to impossible. Graphical passwords are proposed with an option to the user so that he can select an image of his choice and then select some points which is called a click pattern, which is unique to every user.*

Keywords*— *Graphical Password Authentication, Pearsonian Type III Mixture Model, Statistics, Probabilistic model, MIR Flickr.

I. INTRODUCTION- PEARSONIAN TYPE III MIXTURE MODEL

In the earlier research work, we developed and analyzed a model for segmentation based on the mixture Pearsonian Type I Distribution with K-means algorithm. These models are useful when the pixel intensities of the feature vector in the image regions are left skewed. But in some image the pixel intensities of the image regions may not be left skewed. They may have long upper tail with a right skewed nature. To segment these types of images, it is needed to consider that the pixel intensities of the image regions follow a right skewed distribution. Hence, in this research article we develop and analyze image segmentation method based on mixture of Pearsonian Type III Distribution. The Pearsonian Type III Distribution is capable of portraying right skewed and long upper tail distributions. Here, it is assumed that the pixel intensities of each image region follow Type III Pearsonian Distribution and the pixel intensities in the whole image is characterized by a finate mixture of Pearsonian Type III Model.

II. PEARSONIAN TYPE III MIXTURE DISTRIBUTION

In any image analysis, the entire image is considered as a union of several image regions. In each image region the image data is quantified by pixel intensities. The pixel intensity $z = f(x, y)$ for a given point (pixel) (x, y) is a random variable, because of the fact that the brightness measured at a point in the image is influenced by various random factors like vision, lighting, moisture, environmental conditions etc. To model the pixel intensities of the animal and human image regions, it is assumed that the pixel intensities of the region follow a Pearsonian Type III Distribution (PTIIID). The probability density function of the pixel intensity is

$$f_i(z \mid a_i, q_i) = \frac{(q_i a_i)^{(q_i a_i + l)}}{e^{q_i a_i} a\Gamma(q_i a_i + l)} e^{-q_i z_s} \left(l + \frac{z_s}{a_1} \right)^{a_i a_i}, -a_i \le z_s < \infty, -\infty \le q_1 < \infty \qquad \text{(Equation-1)}$$

Where □ is a Gamma Function

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For different values of the parameters the various shapes of probability curves associated with Pearsonian Type III Distribution are shown in Figure-1.

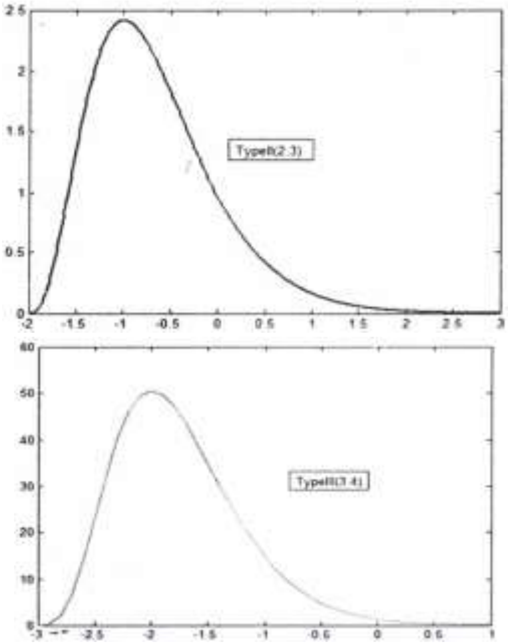

Fig.1: Frequency Curves of Pearsonian Type III Distribution

The entire animal and human image is a collection of regions which are characterized by Pearsonian Type III Distribution. Here, it is assumed that the pixel intensities of the whole image follow a K-component mixture of Pearsonian Type III Distribution and its probability density function is of the form:

$$p(z)=\sum_{i=l}^{K}\alpha_i f_i(z\,|\,a_i,q_i)$$

Where, K is number of regions, $0\le\alpha_i\le 1$ are weights such that $\sum\alpha_i=1$ and is $f_i(z\,|\,a_i,q_i)$ as given in equation (1) α_i is the weight associated with i^th region in the whole image.

In general the pixel intensities in the image regions are statistically correlated and these correlations can be reduced by spatial sampling (Lei T. and Sewehand W. (1992)) or spatial averaging (Kelly P.A.et al (1998)). After reduction of correlation, the pixels are considered to be uncorrelated and independent. The mean pixel intensity of the whole image is $E(Z)=\sum_{i=l}^{K}\alpha_i\mu_i$

III. INDENTATIONS AND EQUATIONS

In this section, it is derived estimates of the model parameters using Expectation Maximization (EM) algorithm. The likelihood function of the observations given by $Z_1, Z_2,\ldots,Z_N$ drawn from an image with probability density function is given in equation – 1.

$$L(\theta)=\prod_{S=1}^{N}p\left(Z_s,\theta^{(1)}\right)$$

That is $L(\theta)=\prod_{S=1}^{N}\left(\sum_{i=l}^{K}\alpha_1 f_i(Z_S,\theta)\right)$

This implies

$$L(\theta)=\sum_{S=l}^{K}\log\left(\sum_{i=l}^{K}\alpha_i f_i(Z_S,\theta)\right)$$

$\alpha_i, i=1,2\ldots,K)$ is the set of parameters

$$\log L(\theta)=\sum_{s=1}^{N}\log\left[\sum_{i=1}^{K}\frac{\alpha_i(q_i a_i)}{e^{q_i a_i}a_i\Gamma(q_i a_i+1)}e^{-q_i z_s}\left[+1\frac{z_s}{a_i}\right]^{q_i a_i}\right]$$

(Equation-2)

The beginning step of the Expectation Maximization algorithm requires the initialization of two parameters ($a_i q_i$; i=1,2,…k) and component weights $(\alpha_i; i=1,2,\ldots,K)$ from the observed values. The idea of EM algorithm is to iteratively calculate Maximum likelihood estimates of unknown parameters

$$\theta=(a_i q_i\alpha_i; i=1,2,\ldots,K)$$

E-STEP :

In the expectation (E) step, the expectation value of log $L(\theta)$ with respect to the initial parameter vector $\theta^{(0)}$

$$Q\left(\theta;\theta^{(0)}\right)=E_{\theta^{(0)}}\left[\log L(\theta)/\bar{z}\right]$$

Given the initial parameters $\theta^{(0)}$, one can compute the density of pixel intensity z_s as

$$p(z_s,\theta^{(1)})=\sum_{i=1}^{K}\alpha_i^{(1)}f_i(z_s,\theta^{(1)}),L(\theta)=\prod_{s=1}^{N}p(z_s,\theta^{(1)})$$

This implies $\log L(\theta)=\sum_{i=1}^{K}\log\left[\sum_{i=1}^{K}\alpha_i f_i(z_s,\theta^{(1)})\right]$

(Equation-3)

The conditional probability of any observation z_s , belongs to any region K is

$$t_k(z_s,\theta^{(1)})=\left[\frac{\alpha_k^{(1)}f_k(z_s,\theta^{(1)}}{p(z_s,\theta^{(1)})}\right]=\left[\frac{\alpha_k^{(1)}f_k(z_s,\theta^{(1)}}{\sum_{i=1}^{K}\alpha_k^{(1)}f_k(z_s,\theta^{(1)})}\right]$$

The conditional of the log likelihood function of the sample is

$$Q\left(\theta;\theta^{(0)}\right)=E_{\theta^{(0)}}\left[\log L(\theta)/\bar{z}\right]$$

Following the heuristic arguments of Jeff A. Bilmes (1997) we have

$$Q(\theta;\theta^{(1)}) = \sum_{i=1}^{K}\sum_{s=1}^{N}(t_i(z_s,\theta^{(1)}))(\log f_i(z_s,\theta^{(1)}) + \log \alpha_i^{(l)}))$$

(Equation-4)

But we have

$$f_i(z/a_i,q_i) = \frac{(q_i,a_i)^{(q_i a_i+1)}}{e^{q_i,a_i} a_i \Gamma(q_i,a_i+1)} e^{-q_i z_s}\left[1+\frac{z_s}{a_i}\right]^{q_i a_i}$$

and

$$Q(\theta;\theta^{(1)}) = \sum_{i=1}^{K}\sum_{s=1}^{N}(t_i(z_s,\theta^{(1)}))((\log f_i(z_s,\theta^{(1)}) + \log \alpha_i^{(l)}))$$

M-STEP:

For obtaining the estimation of the model parameters one has to maximize $Q(\theta;\theta^{(1)})$ such that $\sum_{i=1}^{K}\alpha_i = 1$. This can be solved by applying the standard solution method for constrained maximum by constructing the first order Lagrange type function,

$$s = \left[E(\log L(\theta^{(l)})) + \lambda\left[1-\sum_{i=1}^{K}\alpha_i^{(l)}\right]\right]$$

(Equation-5)

Where, is λ Lagrange multipliers combining the constraint with the log likelihood function to be maximized

Hence, $\frac{\partial S}{\partial \alpha_i} = 0$

This implies

$$\frac{\partial}{\partial \alpha_i}\left[\sum_{i=1}^{K}\sum_{s=1}^{N}(t_i(z_s,\theta^{(1)}))\left[\log\left[\frac{(q_i,a_i)^{(q_i a_i+1)}}{e^{q_i,a_i}a_i\Gamma(q_i,a_i+1)}e^{-q_i z_s}\left[1+\frac{z_s}{a_i}\right]^{q_i a_i} + \log \alpha_i\right]\right]\right] + \lambda\left[1-\sum_{i=1}^{K}\alpha_i\right] = 0$$

This implies

Summing both sides over all observations, we get $\lambda = N$

$$\hat{\alpha}_i = \frac{1}{N}\sum_{s=1}^{N} t_i(z_s,\theta^{(1)})$$

Therefore

The updated equation of for α_i (l+1)th iteration is

$$\alpha_i^{(l+1)} = \frac{1}{N}\sum_{s=1}^{N} t_i(z_s,\theta^{(1)})$$

$$= \frac{1}{N}\sum_{s=1}^{N}\left[\frac{\alpha_i^{(l)} f_i(z_s,\theta^{(1)})}{\sum_{i=1}^{K}\alpha_i^{(l)} f_i(z_s,\theta^{(1)})}\right]$$

(Equation-6)

For updating the parameter a_i ; i=1,2,…k we consider the derivative of $Q(\theta;\theta^{(1)})$ with respect to a_i and equate it to zero.

We have $Q(\theta;\theta^{(1)}) = E[(\log L(\theta^{(l)})]$

Therefore $\frac{\partial}{\partial \alpha_i}Q(\theta;\theta^{(1)}) = 0$

implies $E[(\log L(\theta^{(l)})] = 0$

$$\frac{\partial}{\partial \alpha_i}\left[\sum_{i=1}^{K}\sum_{s=1}^{N}(t_i(z_s,\theta^{(1)})(\log f_i(z_s,\theta^{(1)})+\log \alpha_i^{(l)}))\right]=0$$

$$\frac{\partial}{\partial \alpha_i}\left[\sum_{i=1}^{K}\sum_{s=1}^{N}\left[(t_i(z_s,\theta^{(1)})\right]\left[\log\left[\left[\frac{(q_i,a_i)^{(q_ia_i+1)}}{e^{q_i,a_i}a_i\Gamma(q_i,a_i+1)}e^{-q_iz_s}\left[1+\frac{z_s}{a_i}\right]^{q_ia_i}+\log\alpha_i^{(l)}\right]\right]\right]\right]=0$$

$$\frac{\partial}{\partial \alpha_i}\sum_{i=1}^{K}\sum_{s=1}^{N}\left[(q_ia_i+1)\log(q_ia_i)-\log a_i-q_ia_i-\log(\Gamma(q_ia_i+1))-q_iz_s+q_ia_i\log\left[1+\frac{z_s}{a_i}\right]\right]t_i(z_s,\theta^{(1)})=0$$

$$\sum_{s=1}^{N}[(q_i)\log(q_ia_i)+\frac{(q_ia_i+1)}{q_ia_i}q_i-q_i+q_i\left[\log\left[1+\frac{z_s}{a_i}\right]-\frac{z_s}{a_i+z_s}\right]-q_i\Gamma(q_ia_i+1)t_i(z_s,\theta^{(1)})=0$$

$$\sum_{s=1}^{N}\left[\left[q_i\log\left[q_ia_i\left[\frac{a_i+z_s}{a_i}\right]\right]+\frac{1}{a_i}-\frac{a_iz_s}{a_i+z_s}\right]-q_i\Gamma(q_ia_i+1)\right]t_i(z_s,\theta^{(1)})=0$$

$$\sum_{s=1}^{N}\left[\frac{a_iz_s}{a_i+z_s}+q_i\Gamma(q_ia_i+1)-q_i\log(q_i(a_i+z_s))\right]t_i(z_s,\theta^{(1)})=\frac{1}{a_i}\sum_{s=1}^{N}t_i(z_s,\theta^{(1)})$$

$$a_i=\sum_{s=1}^{N}\frac{t_i(z_s,\theta^{(1)})}{\left[\frac{a_iz_s}{a_i+z_s}+q_i\Gamma(q_ia_i+1)-q_i\log(q_i(a_i+z_s))\right]t_i(z_s,\theta^{(1)})}$$

The updated equation of a_i at $(l+1)^{th}$ iteration is

$$a_i^{(l+l)}=\sum_{s=1}^{N}\frac{t_i\left(Z_s,\theta^{(l)}\right)}{\left[\frac{q_i^{(l)}z_s}{a_i^{(l)}+z_s}+q_i^{(l)}\Gamma\left(q_i^{(l)}a_i^{l}+1\right)-q_i^{(l)}\log\left(q_i^{(l)}a_i^{l}(a_i+z_s)\right)\right]t_i\left(z_s,\theta^{(1)}\right)}$$

$$Where\ t_i\left(z_s,\theta^{(1)}\right)=\frac{\alpha_i^{(1)}f_i\left(z_s,\theta^{(1)}\right)}{\sum_{i=1}^{K}\alpha_i^{(1)}f_i\left(z_s,\theta^{(1)}\right)}$$

For updating the parameter q_i, i=1,2,….,K we consider the derivative of Q
With respect to q_i and equate it to zero

We have $Q(\theta;\theta^{(l)}=E\left[\log L(\theta;\theta^{(l)}\right]$

Therefore $\frac{\partial}{\partial q_i}Q(\theta;\theta^{(l)})=0$ implies $E\left[\frac{\partial\log L(\theta;\theta^{(l)}}{\partial q_i}\right]=0$

$$\frac{\partial}{\partial q_i}\left[\sum_{i=1}^{K}\sum_{s=1}^{N}(t_i\left(z_s,\theta^{(1)}\right)(\log f_i(z_s,\theta^{(1)}+\log\alpha_i^{(l)}))\right]=0$$

$$\frac{\partial}{\partial q_i}\sum_{i=1}^{K}\sum_{s=1}^{N}\left[(q_ia_i+1)\log(q_ia_i)-\log a_i-q_ia_i-\log(\Gamma(q_ia_i+1))-q_iz_s+q_ia_i\log\left[1+\frac{z_s}{a_i}\right]\right]t_i\left(z_s,\theta^{(1)}\right)=0$$

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$$\frac{\partial}{\partial q_i}\sum_{i=1}^{K}\sum_{s=1}^{N}\left[(q_i a_i+1)\log(q_i a_i)-\log a_i-q_i a_i-\log(\Gamma(q_i a_i+1))-q_i z_s+q_i a_i\log\left[1+\frac{z_s}{a_i}\right]\right]t_i\left(z_s,\theta^{(1)}\right)=0$$

$$\sum_{s=1}^{N}\left[\alpha_i\log(q_i a_i)+\frac{(q_i a_i+1)a_i}{q_i a_i}-q_i-z_s+a_i\log\left[1+\frac{z_s}{a_i}\right]-\frac{\int_0^l z_s^{q_i a_i}a_i e^{-z_s}\log z_s dz_s}{\int_0^l z_s^{q_i a_i}a_i e^{-z_s}dz_s}\right]t_i\left(z_s,\theta^{(1)}\right)=0$$

$$\sum_{s=1}^{N}\left[\alpha_i\log(q_i a_i)+\frac{(q_i a_i+1)}{q_i a_i}-(q_i-z_s)+a_i\log\left[1+\frac{z_s}{a_i}\right]-\frac{\int_0^l z_s^{q_i a_i}a_i e^{-z_s}\log z_s dz_s}{\int_0^l z_s^{q_i a_i}a_i e^{-z_s}dz_s}\right]t_i\left(z_s,\theta^{(1)}\right)=0$$

$$\sum_{s=1}^{N}\left[a_i\log\left[q_i a_i\left[\frac{z_s+a_i}{a_i}\right]\right]-(a_i+z_s)+\frac{(q_i a_i+1)}{q_i}-\frac{a_i\Gamma(q_i a_i+1)\psi_0(q_i a_i+1)}{\psi_0(q_i a_i+1)}\right]t_i\left(z_s,\theta^{(1)}\right)=0$$

$$\sum_{s=l}^{N}\left[a_i\log\left(q_i a_i\left(\frac{z_s+a_i}{a_i}\right)\right)-(a_i+z_s)+\frac{(q_i a_i+1)}{q_i}-a_i\Gamma(q_i a_i+1)\right]t_i\left(z_s,\theta^{(1)}\right)=0$$

$$q_i=\frac{\sum_{s=1}^{N}q_i\left[a_i\Gamma(q_i a_i+1)+(a_i+z_s)-a_i\log\left(q_i a_i\left(\frac{z_s+a_i}{a_i}\right)\right)\right]}{a_i\sum_{s=1}^{N}t_i\left(z_s,\theta^{(1)}\right)}-1 \qquad \text{(Equation-7)}$$

The updated equation of q_{il} $(l+1)^{th}$ iteration is

$$q_i^{(l+1)}=\frac{\sum_{s=1}^{N}q_i\left[a_i^l\Gamma\left(q_i^{(l)}a_i^{(l)}+1\right)+\left(a_i^{(l)}+z_s\right)-a_i^{(l)}\log\left(q_i^{(l)}a_i^{(l)}\left(\frac{z_s+a_i^{(l)}}{a_i^{(l)}}\right)\right)\right]}{a_i^{(l)}\sum_{s=1}^{N}t_i\left(z_s,\theta^{(1)}\right)}-1 \qquad \text{(Equation-8)}$$

$$Where\; t_i\left(z_s,\theta^{(1)}\right)=\frac{\alpha_i^{(l+1)}f_i\left(z_s,\theta^{(1)}\right)}{\sum_{i=1}^{K}\alpha_i^{(l+1)}f_i\left(z_s,\theta^{(1)}\right)}$$

IV. K-MEANS CLUSTERTING ALGORITHM

The K-means algorithm is one of the simplest clustering technique for which the objective is to find the partition of the data which minimizes the squared error or the sum of squared distances between all points and their respective cluster centers (Rose H. Turi, (2001)). K-means algorithm uses an iterative procedure that minimizes the sum of distances from each object to its cluster centroid, over all clusters. This evaluational procedure consists of the following steps.

1. Randomly choose K data points from the whole data set as initial clusters. These data points represent initial cluster centroids.
2. Calculate Euclidean distance of each data point from each cluster center and assign the data points to its nearest cluster center.
3. Calculate new cluster center so that squared error distance of each cluster should be minimum.
4. Repeat step II and III until clustering centers do not change.
5. Stop the process.

In the above algorithm, the cluster centers are only updated once all points have been allocated to their closed cluster center. The advantage of K-Means algorithm is that it is a very simple method, and it is based on intuition about the nature of a cluster, which is that the within cluster error should be as small as possible. The disadvantage of this method is that the number of clusters must be supplied as a parameter, leading to the user having to decide what the best number of clusters for the image is (Rose H. Turi, (2001)). Success of K-means algorithm depends on the parameter K, number of clusters in image.

After determining the final value of K (number of regions), we obtain the initial estimates a_i, q_i, and α_i *of* for the ith region using the segmented region pixel intensities with Pearsonian Type III Distribution. The initial estimate a_i, a_i=l/K, where is taken as i=1,2,...,K. The parameters a_i and q_i are estimated by the method of moment's μ_1 as first moment μ_i and its three central moment's μ_2 μ_3 and μ_4.

V. CONCLUSION

The number of image regions is estimated by utilizing the image histogram. The model parameters are estimated by deriving the updated equations of EM algorithm. The initialization of the model parameters is done through K-means algorithm and moment method of estimation. The segmentation algorithm is developed through maximizing the component likelihood under Bayes framework applied in MIR Flickr .

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